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Discount rates and the education gradient in mammography in the UK

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Abstract

I analyse the intertemporal decisions on undertaking breast cancer screening by women aged 50-64 in the UK. I provide estimation results on the discounting of the potential future benefits of screening. I also analyse the education differences in mammography decisions and examine the underlying mechanism how education influences breast cancer screening attendance. Using the institutional settings of the UK, I estimate a structural model, which reveals that although there are differences in the disutility of breast cancer screening along the education level, there is no such difference in the estimated discount factor. The results suggest that the observed education gradient is mainly due to differences in health behaviours and health care attitudes.

JEL Classification: C25, I11, I12

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1 Introduction

This paper analyses the utilisation of breast cancer screening services in the UK. The aims of the paper are to estimate a health discount factor through the analysis of intertemporal health care decisions, and to analyse the role of discounting in determining education differences in breast cancer screening attendance. As the most common method of breast cancer screening is mammography and this is the method the NHS (National Health Service) breast cancer screening programme uses, I use the terms mammography and breast cancer screening interchangeably in this paper. To my knowledge, this is the first paper to estimate the discounting of the potential future benefits of mammography based on European data. The results of this paper indicate forward looking behaviour, and that the education differences in mammography attendance are due to the lower disutility of screening among the more educated rather than differences in time preferences.

The main contribution of the paper is the novel empirical analysis of mammography attendance, based on structural models of utilisation. There is a large number of papers which empirically analyse the utilisation of preventive medical services. People with higher education level are generally found to utilise more preventive health services. This also holds for mammography, as shown by Cutler and Lleras-Muney (2010) for the UK and US, Maxwell et al. (1997) for Canada, and Lee and Vogel (1995) based on data from Texas. However, Moser et al. (2009) do not find a significant effect of education level on breast cancer screening based on data from the National Statistics Omnibus Survey of the UK. My reduced form estimations are also related to Hofer and Katz (1996), Fletcher and Frisvold (2009) and Jusot et al. (2011). These authors analyse different aspects of the socioeconomic gra-

dient in preventive care utilisation. I contribute to this literature by making use of panel observations, and extending the analysis with structural approach. My empirical strategy takes into consideration the institutional settings in the UK.

I use the observed health behaviours of survey respondents to elicit their time preferences. Fuchs (1982) also addresses the relationship between health behaviours, health and time preferences, but he uses survey measures on time preferences. Fang and Wang (2010) provide an empirical analysis of preventive care utilisation based on a dynamic discrete choice model, where individuals are allowed to have hyperbolic discounting, and to be naive about their time-inconsistency. Their application is also on mammography decisions, using data from the Health and Retirement Study. My approach is closely related to that of Fang and Wang, but it is based on different modelling assumptions, leading to different conclusions.

Cutler and Lleras-Muney (2010) and Pol (2011) also investigate the relationship between education, health behaviours and time preferences. They use various data sets from the US, UK and the Netherlands, and find no evidence for differences in discounting or in risk aversion along the education level or for the hypothesis that different time preferences could explain the education-health gradient. My structural estimations can complement the analyses of Cutler and Lleras-Muney and Pol by estimating an education-specific discount factor based on observed health decisions, rather than using proxies for discounting.

The rest of the paper is organised as follows. In section 2 I describe the model that form the basis of the empirical analysis. The data are presented in section 3, and the empirical results and specification checks are discussed in section 4. Section 5 concludes.

2 Model

The start of the breast cancer screening programmes in the UK dates back to 1988.¹ From then, women aged 50-64 are invited for breast cancer screening every third year. The costs of the screening are covered by the NHS, and the screening takes place at one of the static or mobile breast cancer screening units. Since 2004 the age coverage has been extended to 65-70 years. Women aged over 70 can request mammography once every three years, but they are not invited routinely. The frequency of invitations and age categories are the same across the UK. According to the Advisory Committee on Breast Cancer Screening (2006), since November 2001, the invitations support an informed choice in the sense that information is provided not only on the benefits of screening but also on its limitations and risks.²

In this section I present a dynamic discrete choice model of mammography attendance, which is based on the institutional settings in the UK and which forms the basis of my structural estimations. Unlike a static model, a dynamic model makes it possible to estimate the discount factor, which is an important determinant of mammography decisions, given their potential long-run benefits. The model is a semi-parametric long time horizon model, which avoids the heavy dependence on functional form assumptions. The following model is in a sense simpler than the related models of Hotz and Miller (1993) and Fang and Wang (2010) as I assume finite time horizon, do not consider hyperbolic discounting, but utilise the three year recommended frequency of breast cancer screening. The approach of Fang and Wang

¹This summary of institutional background is based on the information provided by the Cancer Research UK (2012).

²The Cancer Research UK (2012) lists three possible harms from breast cancer screening. The first is diagnosing slow growing breast cancers that would never have caused any harm, the second risk is the exposure to small amounts of radiation during screening, and the third is the unnecessary anxiety in women who are called back for more tests, but found not to have breast cancer.

is not applicable to the UK sample as women in the UK generally do not have to make decisions on mammography each year.

The decision to make is whether to attend a due screening. A screening is defined to be due if a woman in the target age category did not attend a screening during the previous two years. I assume that the screening decision is made once every three years, thus both attending and not attending a due screening imply no further screening in that three year time period. This assumption corresponds to the institutional settings in the UK, and this makes the value function different from standard Bellman equations, as presented e.g. by Magnac and Thesmar (2002). In section 4.4.3 I check the robustness of the results to this assumption by allowing for postponed and repeated screenings. The attendance decision is influenced via three channels: the disutility of screening, the effect of screening on survival probability, and the discount factor. In the empirical model, education is allowed to influence the mammography decision via its effect on the disutility of screening and on the discount factor.

Let $i \in \{0, 1\}$ denote the choice options on utilisation, $x \in X$ the observable state variables (e.g. education level, living area), and $\varepsilon_0, \varepsilon_1$ the choice specific preference shocks which have type-I extreme value distribution.³ The discount factor is δ . Based on the institutional settings before 2004, a woman aged 62-64 could make the attendance decision with presuming that she would not have to attend any further screenings. Let's assume that the maximum possible lifetime is A , then the value functions of a woman aged $a \in \{62, 63, 64\}$

³The cumulative distribution function of type-I extreme value distribution is:

$$P(X \leq x) = \exp\left(-\exp\left(\frac{x - \mu}{\sigma}\right)\right).$$

Train (2009) provides an overview of the usage of the type-I extreme value distribution in logit models.

are:

$$V^a(x, i = 0) = u(x, i = 0) + \sum_{t=0}^{A-a} \delta^t \left(\sum_{x' \in X} u(x', i = 0) \pi_a^{a+t}(x'|x, i = 0) \right), \quad (1)$$

$$V^a(x, i = 1) = u(x, i = 1) + \sum_{t=1}^{A-a} \delta^t \left(\sum_{x' \in X} u(x', i = 0) \pi_a^{a+t}(x'|x, i = 1) \right), \quad (2)$$

where $\pi_a^{a+t}(\cdot)$ is the transition probability from age a to $a + t$, and $u(\cdot)$ is the instantaneous utility of life - this utility is derived from the state variables and the usage (or no usage) of mammography. In the empirical specification the transition probability is simply the survival probability. Using the distributional assumption, these two value functions determine the probability of attendance at ages 62-64:

$$P^a(x) = \Pr[V^a(x, i = 1) + \varepsilon_1 \geq V^a(x, i = 0) + \varepsilon_0] = \frac{\exp[V^a(x, i = 1)]}{\exp[V^a(x, i = 0)] + \exp[V^a(x, i = 1)]}. \quad (3)$$

This derived probability can be used in the value functions at ages 59-61, which in turn again determine the attendance probability at these ages. This can be used in the value functions at ages 56-58, and so on. Thus in an iterative way all the attendance probabilities can be

determined. The value functions for ages $a \in [50, 61]$ are:

$$\begin{aligned}
V^a(x, i = 0) = & u(x, i = 0) + \delta \sum_{x' \in X} u(x', i = 0) \pi_a^{a+1}(x'|x, i = 0) + \\
& + \delta^2 \sum_{x' \in X} u(x', i = 0) \pi_a^{a+2}(x'|x, i = 0) + \delta^3 \sum_{x' \in X} \pi_a^{a+3}(x'|x, i = 0) \cdot \\
& \cdot [P^{a+3}(x') V^{a+3}(x', i = 1) + (1 - P^{a+3}(x')) V^{a+3}(x', i = 0)], \quad (4)
\end{aligned}$$

$$\begin{aligned}
V^a(x, i = 1) = & u(x, i = 1) + \delta \sum_{x' \in X} u(x', i = 0) \pi_a^{a+1}(x'|x, i = 1) + \\
& + \delta^2 \sum_{x' \in X} u(x', i = 0) \pi_a^{a+2}(x'|x, i = 1) + \delta^3 \sum_{x' \in X} \pi_a^{a+3}(x'|x, i = 1) \cdot \\
& \cdot [P^{a+3}(x') V^{a+3}(x', i = 1) + (1 - P^{a+3}(x')) V^{a+3}(x', i = 0)]. \quad (5)
\end{aligned}$$

In the empirical analysis I normalise $u(x, i = 1) = 0$, that is I estimate the influencing factors of $u(x, i = 0) - u(x, i = 1)$, which I call the disutility of screening. The prerequisites of identification are based on Magnac and Thesmar (2002), and are similar as in the model of Fang and Wang (2010). The model is identified only if there is at least one variable which affects the transition probabilities, but which has no influence on the disutility of screening (i.e. no influence on $u(x, i = 0) - u(x, i = 1)$). Without this restriction the δ parameter could be identified only by functional form. The model is estimated with the method of maximum likelihood. In section 4.2 I use objective health indicators and the number of GP visits for identifying δ , allowing subjective health to influence the relative utility of screening. I discuss there the estimation method and the exclusion restrictions in more details.

3 Data

The empirical analysis is based on the British Household Panel Survey (BHPS), waves 1-18. This is an annual survey, which begun in 1991. The survey covers each adult member of a representative sample of more than 5,000 households from the UK. I restrict the sample to female respondents aged 50-64 - corresponding to the initial target age category of the screening programme. The sample is considered to be representative for women who haven't been diagnosed with cancer.⁴

In Table 1 I provide descriptive statistics of the restricted sample. The education categories are based on the International Standard Classification of Education (ISCED) codes provided in the BHPS data. Secondary education corresponds to having at least lower secondary education but no degree (ISCED levels 2, 3a, 3c, 5b). Higher education corresponds to having at least first degree (ISCED levels 5a, 6). Schneider (2008) provides an overview of the ISCED coding of UK's education qualifications. As only 8% of the respondents in the applied subsample have higher education, and the cutoff between the secondary and higher education categories is not straightforward, in the empirical analysis I use a binary indicator of having secondary or higher education. Although the BHPS provides information on the years of schooling of the respondents, I use the categorical indicators of education level as those are less subject to measurement errors. The indicator of working equals one in case

⁴It would be reasonable to exclude those respondents from the sample who have been diagnosed with cancer, since after such a diagnosis the need for health check-ups substantially changes. However, such a restriction cannot be done for the first 10 waves of the survey due to missing information on cancer. Based on waves 11-18 only around 2% of the female respondents aged 50-64 report having any type of cancer. It is likely that due to attrition among respondents diagnosed with cancer, the actual prevalence rate of breast cancer is higher. Based on statistics provided by Maddams et al. (2009), about 500 thousand individuals lived with breast cancer in 2008 in the UK, the prevalence rate was around 2.7% in the female population aged 45 – 64, and 5.7% in the female population aged 65 and above.

of self employment or paid employment. The binary measure of smoking is based on the question "do you smoke cigarettes" - in wave 9 the question is formulated in a different way, therefore for the sake of comparability I do not use the information provided in wave 9. The indicator of good health equals one if the respondent reports excellent or good health status,⁵ and the indicator of financial difficulties is one if she reports difficulties or reports "just about getting by." Chest and stomach problems, and diabetes are included in the empirical analysis as those are asked in all waves of BHPS, are relatively prevalent conditions, and are reasonably included in the survival probability models. The number of GP visits is provided in the data by a categorical variable ranging from 1 to 5, where 1 corresponds to no GP visits since September of the previous year and 5 corresponds to more than ten visits. The dental check-up indicator equals one if a respondent reports having a dental check-up since last year's September.

Table 1 here

The basic indicator of utilisation equals one if the respondent reports breast cancer screening since September of the year before the survey fieldwork started. I use this as a noisy measure of attendance within the past twelve months.⁶ Figure 1 illustrates breast cancer screening attendance by age. Attending screening is the most likely by the age group 50-70,

⁵Apart from wave 9, the survey asks about the health over the last 12 months, compared to people of the same age. In wave 9 the survey asks about the general health status, without further specification, and about the change in health status compared to the previous year. Because of these differences, I do not use the information provided in wave 9 (similarly to the indicator of smoking).

⁶The BHPS fieldwork dates were between September of a given year and January/April/May of the next year - the ending of the fieldwork varied across the survey waves. For example, the fieldwork of wave 12 lasted from 1 September 2002 to 30 April 2003, and respondents were asked if they had breast screening since 1 September 2001. Thus the question refers to the past 12-20 months, depending on the date of the interview. If screenings are evenly distributed throughout the year then it is more likely for respondents interviewed later to report screening. This measurement error follows from the survey design and due to its random nature it should not bias the results of this paper.

in line with the NHS recommendations. 34% of the female respondents in the 50-64 age group report attending breast cancer screening in the previous year. 96% of all women who report screening indicate that it was provided by the NHS.

Figure 1 here

4 Empirical analysis

4.1 Reduced form estimation

In this section I estimate pooled cross sectional OLS models of screening. The aim is to provide an overview on the individual level influencing factors of mammography use. The limitation is that the reduced form model cannot reveal the actual influencing mechanisms and time preferences, which will be analysed based on the structural models.

I restrict the sample to those respondents who have due breast cancer screening, i.e. who did not report mammography attendance in the previous two survey waves.

In Table 2 I report the reduced form estimation results. The standard errors are clustered on the individual level. I start with including only age and education level as regressors. Then I extend the control variables with further socioeconomic and health indicators. In the third specification I also control for GP and dental visits. Although dental care is generally not provided free of charge in the UK, I still consider reporting a dental check-up as an indicator of health care attitudes because of two reasons. First, the survey asks specifically about dental check-ups and not dental treatments, and the NHS provides dental check-ups at low cost. Second, the most vulnerable groups are entitled to free dental care.

An education gradient can be observed: those with secondary or higher education are *ceteris paribus* more likely to attend a due screening. This relation becomes weaker and statistically insignificant if the indicators of other health care use are included. This suggests that the education gradient is not specific to breast cancer screening, but it is a general phenomenon of preventive care, or more generally of health care utilisation. The included characteristics can explain only little part of the within and between individual variation in utilisation.

Table 2 here

4.2 Structural estimation - long time horizon

In this section I estimate the model described in section 2. I restrict the estimating sample to females aged 50-64 who have due breast cancer screening. I apply a two-step estimation method. In the first step I estimate the transition probabilities, and in the second step I estimate the discount factor and the parameters of the utility function. I specify the disutility of screening as a linear function of the observable characteristics, and assume that the only uncertainty is survival. Apart from age I treat the other observable characteristics as fixed throughout time. With this simplification I consider the screening to have the sole purpose of increasing longevity through the early diagnosis of breast cancer. I neglect the health benefits of screening due to early diagnosis, but also miss the negative health effects due to false positives and related anxiety.

I set the maximum lifetime to age 104, i.e. the time horizon varies between 40-54 years, depending on the age when the screening decision is made. As the first step of the estimation,

I estimate a logit model of one-year survival, and predict the survival probability with and without breast cancer screening for each individual in the sample. Apart from attending the due screening, I include age, working status, smoking, reporting good health, chest and stomach problems, diabetes, and the indicator of the number of GP visits in the previous year. The number of GP visits and the three objective health indicators are excluded from the second stage model of instantaneous utility. The underlying assumption is that these indicators affect the survival probability and the utility level as well, but not the disutility attached to screening. The disutility of screening is allowed to be influenced by the reported subjective health. The exclusion restrictions are needed for the identification of the discount factor. In section 4.4.2 I present some robustness checks on the excluded variables.⁷

I report the logit model estimates in Table 3. The two-year survival probability estimates will be used in section 4.4.1. Without screening, the average predicted one-year survival probability is 99.2%. Based on the average marginal effects, mammography has statistically significant but less than one percentage point increasing effect on the survival probability. As the potential benefits of breast cancer screening on survival probability are likely to be in the long run, these estimates cannot capture the total benefits of screening. On the other hand, omitted variables (unobserved health behaviours related to screening) might cause upward bias in the estimated effects. Although I estimate here the short run effect of a single screening, this estimate can still capture the effect of regular mammography. The data indicate that if a woman in the target age category did not attend a due screening three

⁷To improve the explanatory power of the logit model of survival and to support the identification of the second stage of the structural model I extended the models of survival with birth year effects and with age specific effects of screening. However, these additional regressors were insignificant, therefore are not reported here. Being in a hospital could also be a strong predictor of survival, but hospitalised people are not interviewed in the survey, only a proxy interview is conducted then.

years before then her probability of attendance this year is on average 20.5%. However, if she attended the last due screening then the current probability of attendance is 62.4%. Thus attending a due screening generally implies regular attendance.⁸

Table 3 here

If the beneficial effect of screening in terms of survival probability is overestimated then that leads to a downward bias in the estimated discount factor. This might be the case with the long run estimates, as discussed in section 4.3. Although there are various results in the literature on the potential benefits of mammography screening, it is difficult to find directly comparable estimates. The Agency for Healthcare Research and Quality (2009) report that mammography screening reduces breast cancer mortality by around 15% at ages 39-59, and by around 30% at ages 60-69. The Cancer Research UK (2012) claim that breast cancer screening can save 500 – 1,400 lives per year in the UK.⁹ Many studies find small but positive effect of breast cancer screening on longevity (among others Stout et al. (2006), Mandelblatt et al. (2009), Glasziou and Houssami (2011)). Fang and Wang (2010) also find that undertaking mammography significantly reduces the two-year probability of dying. On the other hand, Gotzsche and Olsen (2000) state that there is no evidence that breast cancer screening would decrease mortality due to breast cancer.

⁸Nonrandom attrition can bias the estimation results if the effects of the included variables on survival differ between those who fall out of the sample (due to factors other than death) and those who remain in the sample. The attrition rate per wave due to reasons other than death is around 5% in the subsample of women aged 50-64. The attrition and its explanatory factors in the BHPS data are discussed in details by Uhlig (2008), and Jones et al. (2006) provide evidence for health related attrition in the BHPS. However, in the estimated models of survival there is no clear evidence that the effect of screening would vary with health level, thus it can be assumed that attrition due to bad health does not cause considerable bias in the results. However, if people diagnosed with cancer are less likely to respond then the positive effect of screening might be underestimated since then the benefits of screening through early diagnosis is not observed.

⁹The Cancer Research UK (2012) also provides some statistics on the survival probabilities of different stages of breast cancer. For example, while the 5-year survival probability of stage 1 breast cancers is more than 90%, the survival probability of stage 3 breast cancers is only around 50%. These statistics also indicate that early diagnosis of cancer can significantly decrease mortality in the short run.

I generate the longer and future survival probabilities by multiplying the appropriate age-specific one-period survival probabilities. If the current one-period survival probability is estimated to be $S\left(X\hat{\beta} + \hat{\beta}_{age} \cdot age\right)$, then the generated k -period survival probability at age A is $\prod_{t=0}^k S\left(X\hat{\beta} + \hat{\beta}_{age} \cdot (A + t)\right)$.

The specification of the survival probability assumes that the benefits of a screening accumulate over time. A simple data check provides some evidence for the reasonability of this assumption. I re-estimate the logit model of survival from one up to ten years of survival. The average marginal effect of mammography increases gradually from 0.005 (one-year survival, t statistics 2.86) up to 0.050 (ten-year survival, t statistics 3.08). However, these estimates can capture the effects of later screenings and other health behaviours, as well. If I estimate the same models on the subsample of women aged 62-64 in years 1991-1996, that is who were unaffected by the age extension thus no further screening can be assumed, the pattern remains similar, although the marginal effects become larger: 0.007 (two-year survival, t statistics 0.30 - the effect on one-year survival cannot be estimated on this restricted sample) up to 0.120 (ten-year survival, t statistics 2.40). In section 4.4.3 I present a specification check where I use the estimated survival probabilities up to ten years.

The second step is the maximum likelihood estimation of the utilisation model. In order to simplify the estimation procedure, the value functions of equations (4) and (5), and the attendance probabilities are calculated only for ages 51, 54, 57, 60, and 63, and these are assigned to the closest age values. The estimation sample is restricted here to observations before 2004. Since 2004 women aged above 64 are also invited to breast cancer screening, therefore the assumptions behind equations (1) and (2) do not hold any more.

I include the following indicators in the function of the relative disutility of breast cancer

screening: age, secondary or higher education level, being married, reporting good health, smoking, and living in Scotland, Wales, or Northern Ireland. Thinking in terms of a linear utility function with interaction terms, those variables should be included in the model of relative disutility which are interacted with the indicator of screening in the model of utility level.¹⁰ These can be variables which capture the time and travel cost of screening (age, living area), the apprehension against screening and the pleasure derived from acting health consciously (education, marital status, smoking), or the perceived discomfort of screening (age, subjective health status). So as to reduce the noise in the estimation results, I exclude those observable characteristics which could be considered as influential in the relative disutility of screening, but are estimated to have a coefficient with a high p-value (labor force status), or have little variation across the respondents (being widowed, having children). Also, for the sake of identifying the parameters of screening disutility, having GP visits and reporting objective health problems are included in the survival probability model, but not in the model of relative disutility. These exclusions are based on the following considerations. Objective health problems can influence the beneficial effect of breast cancer screening, however, the discomfort of screening is likely to be influenced by how the patient feels in general, i.e. by the subjective health status. The same argument holds for GP visits, if we consider the number of such visits as an additional measure of objective health. Also, since the GP practices and screening units are generally not at the same location, visiting a GP does not reduce the marginal time cost of having a mammography. In section 4.4.2 I discuss the possible limitations of these assumptions, and also present some robustness checks with

¹⁰Using the linearity assumption, the instantaneous utility levels without and with screening are: $u(x, i = 0 \text{ or } 1) = X\alpha - \gamma_0 i - X\gamma i$, where γ_0 is the disutility of screening, which might be amplified or moderated by the X variables (captured by the $X\gamma$ term). Thus the overall disutility of screening is $u(x, i = 0) - u(x, i = 1) = \gamma_0 + X\gamma$.

respect to the included variables in the model of relative disutility.

In the basic specification I estimate a single parameter of discount factor, whereas in the extended specification I allow the discount factor to differ between the two education categories. The estimated parameters are reported in Table 4. I do not include the insignificant indicators of living in Wales or Northern Ireland in the second specification. The standard errors are clustered on the individual level, and the Murphy-Topel correction is applied to the standard errors, following Greene (2003) and Hardin (2002). Due to the small variation in the observed survival and to the complex setup of the likelihood function, the two-step estimation procedure is preferred here.¹¹

Table 4 here

4.3 Discussion

Based on the structural estimation results, the average relative disutility of attendance is positive, indicating that mammography has non-pecuniary costs (e.g. discomfort, time costs). The results suggest that the education differences in mammography decisions are likely to be driven by the different disutility attached to mammography. Those who have secondary or higher education level are estimated to derive less utility from missing a due breast cancer screening. This difference is significant at the 1% significance level.¹² As in

¹¹The second step of the maximum likelihood model is estimated with the *ml* and *ml maximize* commands of Stata 12.1. I use the Davidon-Fletcher-Powell (DFP) and Broyden-Fletcher-Goldfarb-Shanno (BFGS) quasi-Newton algorithms, switching between the two after five iterations. The models require 18 – 20 iterations.

The likelihood function is specified as follows. First, I generate the age-specific value functions and attendance probabilities following equations (1)-(5). The transition probabilities in these equations are the survival probabilities generated in the first step of the estimation. Next, the likelihood function is generated as multiplying over the observations the expression of $P(x)^{I(i=1)}(1 - P(x))^{1-I(i=1)}$, where $P(x)$ is the attendance probability, and $I(i = 1)$ is the binary indicator of attending the screening.

¹²Investigating in details the other parameters of the disutility function is out of the scope of this paper.

Fletcher and Frisvold (2009), the differences along education can be caused by different occupations and different level of information, among others. Although the opportunity cost of screening is likely to increase with education, the cost of illness might also increase. More educated women might be more informed about the potential benefits of screening and might have positive attitudes towards preventive care in general.

The discount factor estimate suggests that women heavily discount the long run benefits of mammography. There are more possible explanations for this results: the time horizon is shorter than the assumed 40-54 years, the long run survival benefits of mammography are strongly overestimated, or the benefits of a single screening are overestimated as the estimates rather capture the benefits of regular screening attendance. Some of the specification checks of sections 4.4.1 and 4.4.3 address these issues. The estimated discount factor is close to the result of Fang and Wang (2010), even though they use US data and different modelling assumptions. There is no significant difference in the discount factor between the two education groups, although women having secondary or higher education are estimated to have a lower discount rate. Testing the equality of the two discount factors yields a t statistic of 0.42.

4.4 Specification checks

4.4.1 Short time horizon

The model estimated in this section assumes a time horizon of three years. Although the limited time horizon is a restriction, that is worthwhile to analyse empirically as long run survival probabilities with and without screening are difficult to estimate. Using the nota-

tions and distributional assumption of section 2, the choice-specific value functions at age a are:

$$\begin{aligned} V(x, i = 0) &= u(x, i = 0) + \delta \sum_{x' \in X} u(x', i = 0) \pi_a^{a+1}(x'|x, i = 0) + \\ &\quad + \delta^2 \sum_{x' \in X} u(x', i = 0) \pi_a^{a+2}(x'|x, i = 0), \end{aligned} \quad (6)$$

$$\begin{aligned} V(x, i = 1) &= u(x, i = 1) + \delta \sum_{x' \in X} u(x', i = 0) \pi_a^{a+1}(x'|x, i = 1) + \\ &\quad + \delta^2 \sum_{x' \in X} u(x', i = 0) \pi_a^{a+2}(x'|x, i = 1), \end{aligned} \quad (7)$$

and the probability of utilising preventive care is:

$$P(x) = \Pr[V(x, i = 1) + \varepsilon_1 \geq V(x, i = 0) + \varepsilon_0] = \frac{\exp[V(x, i = 1)]}{\exp[V(x, i = 0)] + \exp[V(x, i = 1)]}. \quad (8)$$

The prerequisites of identification are the same as in the model with long run horizon.

As the first step of the estimation, I estimate logit models of one- and two-year survival, and predict the survival probabilities with and without breast cancer screening.

I present in Table 5 the second stage estimation results. The estimated disutility parameters are close to the estimates with long time horizon, as presented in Table 4. Again, having secondary or higher education is estimated to significantly decrease the disutility attached to breast cancer screening.

Once I assume short time horizon, the estimated discount factor becomes larger than one. Omitting the long run benefits of breast cancer screening from the empirical model increases the estimated discount factor considerably up to a doubtful level, which suggests that individuals are in fact forward looking when making decisions on breast cancer screening.

Thus the long time horizon assumption of section 2 is reasonable. The high discount factor can also indicate that people overestimate the potential benefits of mammography. This can be partly due to the information received from the supply side, e.g. via the invitation letters or from the GP.¹³ Again, I find no evidence that the discount factor would significantly differ between the two education categories, thus the differences in utilisation are not driven by different time preferences.

Table 5 here

4.4.2 Long time horizon, variables included

In this section I analyse the robustness of the results under the assumption of long time horizon, as presented in section 4.2. In particular, I check the robustness of the results presented in the first column of Table 4 with respect to the variables included in the model.

As the first robustness check I replace the binary indicator of education with the years of schooling. I censor the reported years of schooling at 30. The so generated schooling variable has mean of 13.3 and standard deviation of 4.3 in the analysed sample. In this specification the coefficient of the years of schooling is -0.005 (t statistics 0.70), and the discount factor is 0.682 (t statistics 7.35). Thus the discount factor is robust to this modification. The estimated coefficient of the years of schooling is negative but statistically insignificant, which reflects that this indicator of education is a noisy measure. If the reported years of schooling is censored at lower ages then its estimated coefficient increases in absolute value, and its significance also becomes slightly stronger. If two binary schooling indicators are included,

¹³In an analysis of vaccination take-up, Maurer (2009) shows that supply channels (physician quality, among others) have important influencing role on the take-up decision.

one for having secondary education only, and one for having higher education then the coefficient of the first one is close to the earlier estimates (-0.201 with t statistics of 2.28), whereas the coefficient of the higher category is small and statistically insignificant. The discount factor in this specification is 0.691 (t statistics 5.96).

The main results of the next set of robustness checks are presented in Table 6. In specification (1) I assume that having visited a GP the previous year influences the instantaneous disutility of breast cancer screening. This assumption can be reasonable if the GPs can attenuate the potential apprehension of patients against mammography, or if GP visits capture attitudes towards health care and thus imply lower disutility of screening. I include a binary indicator of reporting any GP visits, which equals one for 77% of the respondents in the sample used. In specification (2) I include the binary indicator of dental check-ups in the model of disutility attached to mammography. Visiting a dentist can capture general attitudes towards preventive care, without having influence on the survival probability. I do not include this variable in the benchmark specification since I am interested in the overall effect of education, which can include general preventive care attitudes. In the disutility part of the model, both the binary variable of GP visits (specification (1)) and of dental visits (specification (2)) are significantly negative, indicating common influencing factors of mammography attendance and the use of these services. In specification (3) I check the importance of the exclusion restrictions. If there are no exclusion restrictions then the model can be still estimated, but the identification is based on the functional form. In this specification none of the objective health indicators are significant in the disutility part of the model. Finally, in specification (4) I reestimate the benchmark long run horizon model with excluding the subjective health measure both from the survival probability part and

the utility part of the model. Crossley and Kennedy (2002) provide evidence that survey measures of self-assessed health are subject to measurement error, thus including them can bias the estimates.

As presented in the upper half of Table 6, apart from specification (2), the negative and statistically significant effect of secondary or higher education level on the disutility of screening is a robust finding. Once dental care is included as an explanatory variable then the coefficient of education becomes insignificant at 10% significance level, and smaller in absolute value. This indicates that more educated women attach smaller disutility to breast cancer screening because of generally more positive attitudes towards or better access to health care. Thus the education gradient is not a unique feature of mammography. This is in line with the reduced form estimates of section 4.1. Except for specification (3), the estimated discount factor is qualitatively robust to the alternative specifications. The robustness of the discount factor holds only if that is identified not only by functional form, but also with the help of exclusion restrictions.

Table 6 here

4.4.3 Long time horizon, modelling assumptions

In the following I check the sensitivity of the benchmark maximum likelihood estimation results to the modelling assumptions. My focus is still on the long time horizon model, as presented in section 4.2

First, I take into account that some respondents have to attend a mammogram within the next two years after the screening, and also that some respondents who do not attend a due screening just postpone it. I use the observed ratios of repeated and postponed screening:

26% and 18% of the respondents attend a screening one and two years after attending a due breast cancer screening, and 25% and 22% attend a screening one and two years after a missed due screening. Thus the probability of realising the relative utility of non-attendance one and two years after the screening decision is one minus the probability of repeated (if attended) or postponed (if not attended) screening. In equations (4) and (5) I re-scale the one and two years ahead utility levels with the so generated probabilities of non-attendance. I assume here that the probabilities of repeated and postponed screening are exogenously determined, the same for everyone, and zero after age 64. As row (5) of Table 6 shows, the key parameter results are robust to this specification.

The main empirical caveat of the model with long time horizon is that it is difficult to estimate the effect of mammography on the long run survival probabilities. Until now I used the estimated one-period survival probabilities to generate the survival probabilities to later periods. This implies that a screening can have positive effect even after 40 years. Thus it is likely that the positive effects of screening are overestimated, which can lead to a downward bias in the discount rate. I conduct a set of robustness checks to analyse the sensitivity of the results to the assumptions on survival probability. These results are also presented in Table 6.

In specifications (6-7) I assume that the time horizon extends up to age 79-81 ($A - a = 17$ years in equations (1) and (2)) or up to 69-71 ($A - a = 7$ years in equations (1) and (2)), implying that the screening has negligible effect on the survival probabilities to older ages. This modification has little effect on the magnitude of the education coefficient. In line with the results of section 4.4.1, the estimated discount factor increases with shorter time horizon, although based on these estimates it is not possible to determine the true exact length of

time horizon. Next, in specification (8) I estimate the survival probabilities with and without screening up to 10 years, and correspondingly limit the time horizon in the model up to 10 years. The influencing factors in these logit models of survival are the same as before, and I estimate these logit models on the whole 50-64 female population. As discussed in section 4.2, these estimates can capture the effects of later screenings, and due to attrition the estimation results of the survival models become less reliable with longer time horizon. Nevertheless, the estimated parameters of the utility model are comparable to the benchmark results.

In the final specification check I relax the assumption that labour force status would be constant throughout the time horizon of the decision maker. Here I consider the non-working status as an absorbing state, whereas those who are working are assumed to plan to retire at age 65. In the BHPS pooled sample less than 10% of the women work above this age. Thus the generated k -period survival probability at age A is the same as before if $A + k \leq 65$ or if someone is retired, otherwise it becomes $\prod_{t=0}^{65-A} S(X\beta + \beta_{age} \cdot (A + t)) \cdot \prod_{t=65-A+1}^{65-A} S(X\beta - \beta_{work} + \beta_{age} \cdot (A + t))$, where β_{work} is the coefficient of the working dummy, which is also included in the β vector of parameters. As row (9) of Table 6 shows, this extension of the model has little effect on the key estimated parameters.

5 Concluding remarks

In this paper I analysed the mammography attendance of women aged 50-64 in the UK. My aims were to estimate the discount factor implied by mammography decisions, and to analyse the education differences in utilisation. The empirical analysis was based on the British Household Panel Survey.

Reduced form estimation results suggest that the observed education gradient is mainly due to differences in health behaviours and health care attitudes, and not due to different attitudes towards or access to breast cancer screening in particular. Structural estimates reveal that although there are differences in the disutility of breast cancer screening along the education level, there is no such difference in the estimated discount factor. Accordingly, differences in the utilisation of preventive services across different education groups are rather the consequences of attitudes towards and conceptions about these services, and not of the potentially different time preferences. This suggests that the education differences in mammography attendance could be mitigated by information campaigns aimed at the lower educated.

The general finding in the literature is that higher educated people have on average lower discount rates, for example such result is found by Lawrance (1991) based on data on consumption dynamics, Warner and Pleeter (2001) based on choices between annuities and lump-sum payments in a military downsizing programme, and Harrison et al. (2002) based on a Danish field experiment. Comparing these with my results on the discounting of health costs and benefits suggests that individuals can have considerably different health discount rates and monetary discount rates, and educational differences are more influential on the monetary discount rates.

The estimated one-year discount factor is around two if a time horizon of three years is assumed, 0.85 with time horizon up to age 70, and 0.69 with time horizon up to around age 100. The results and specification checks imply that the benefits of mammography are realised in the long run, and women take into consideration the long term benefits when making a decision on attending a screening. However, the estimation results also suggest

that women might overestimate the potential benefits of breast cancer screening, leading to over-utilisation. Since there is no evidence whether mammography attendance is higher or lower than what is reasonable according to its benefits and risks, it is desirable that the recommended frequency and age category of women screened should be revised regularly according to the latest medical evidence.

The results of this paper are based on a set of simplifying assumptions, which are necessary due to data limitations and for the sake of the estimability of the empirical models. Among others, the long run effects of breast cancer screening on mortality are derived from the short run effects, and I assume that the only uncertainty is survival. Acknowledging these limitations, this analysis can be considered as a simple step towards getting more insights into the demand for breast cancer screening.

References

Advisory Committee on Breast Cancer Screening. 2006. "Screening for Breast Cancer in England: Past and Future." NHS Breast Screening Programme (NHSBSP) Publication, No. 61.

Agency for Healthcare Research and Quality. 2009. "Screening for Breast Cancer: Systematic Evidence Review Update for the U. S. Preventive Services Task Force." Evidence Review Update, No. 74. *AHRQ Publication*, No. 10-05142-EF-1.

Cancer Research UK. 2012.

<http://cancerhelp.cancerresearchuk.org/type/breast-cancer/about/screening/mammograms-in-breast-screening>,

<http://info.cancerresearchuk.org/cancerstats/types/breast/screening/history/>,

<http://www.cancerresearchuk.org/cancer-help/type/breast-cancer/treatment/statistics-and-outlook-for-breast-cancer>,

<http://www.cancerresearchuk.org/cancer-help/about-cancer/cancer-questions/what-the-breast-screening-review-means#down>

Crossley, T. F. and S. Kennedy. 2002. "The reliability of self-assessed health status." *Journal of Health Economics*, 21: 643–658.

Cutler, D. M., and A. Lleras-Muney. 2010. "Understanding differences in health behaviors by education." *Journal of Health Economics*, 29: 1–28.

- Fang, H. and Y. Wang. 2010. "Estimating Dynamic Discrete Choice Models with Hyperbolic Discounting, with an Application to Mammography Decisions." *NBER Working Paper*, No. 16438.
- Fletcher, J. M. and D. E. Frisvold. 2009. "Higher Education and Health Investments: Does More Schooling Affect Preventive Health Care Use?" *Journal of Human Capital*, 3(2): 144-176.
- Fuchs, V. R. 1982. "Time Preference and Health: An Exploratory Study." In: *Economic Aspects of Health*, ed. V. R. Fuchs. University of Chicago Press.
- Glasziou, P. and N. Houssami. 2011. "The evidence base for breast cancer screening." *Preventive Medicine*, 53: 100-102.
- Gotzsche, P. C., and O. Olsen. 2000. "Is screening for breast cancer with mammography justifiable?" *Lancet*, 355: 129–134.
- Greene, W. H. 2003. *Econometric Analysis*. Fifth edition. Prentice Hall, Pearson Education International.
- Hardin, J. W. 2002. "The robust variance estimator for two-stage models." *The Stata Journal*, 2: 253-266.
- Harrison, G. W., M. I. Lau and M. B. Williams. 2002. "Estimating Individual Discount Rates in Denmark: A Field Experiment." *The American Economic Review*, 92(5): 1606-1617.

- Hofer, T. P., and S. J. Katz. 1996. "Healthy Behaviors among Women in the United States and Ontario: The Effect on Use of Preventive Care." *American Journal of Public Health*, 86 (12): 1755-1759.
- Hotz, V. J., and R. A. Miller. 1993. "Conditional Choice Probabilities and the Estimation of Dynamic Models." *The Review of Economic Studies*, 60(3): 497-529.
- Jones, A.M., X. Koolman, and N. Rice. 2006. "Health-related non-response in the BHPS and ECHP: using inverse probability weighted estimators in nonlinear models." *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 169(3): 543-569.
- Jusot, F., Z. Or, and N. Sirven. 2011. "Variations in preventive care utilisation in Europe." *European Journal of Ageing*, forthcoming.
- Lawrance, E. C. 1991. "Poverty and the Rate of Time Preference: Evidence from Panel Data." *Journal of Political Economy*, 99(1): 54-77.
- Lee, J. R-J., and V. G. Vogel. 1995. "Who Uses Screening Mammography Regularly?" *Cancer Epidemiology, Biomarkers and Prevention*, 4: 901-906.
- Maddams, J. et al. 2009. "Cancer prevalence in the United Kingdom: estimates for 2008." *British Journal of Cancer*, 101: 541 – 547.
- Magnac, T., and D. Thesmar. 2002. "Identifying Dynamic Discrete Decision Processes." *Econometrica*, 70(2): 801-816.

- Mandelblatt, J. S. et al. 2009. "Effects of Mammography Screening Under Different Screening Schedules: Model Estimates of Potential Benefits and Harms." *Annals of Internal Medicine*, 151: 738-747.
- Maurer, J. 2009. "Who has a clue to preventing the flu? Unravelling supply and demand effects on the take-up of influenza vaccinations." *Journal of Health Economics*, 28: 704–717.
- Maxwell, C. J. et al. 1997. "Factors important in promoting mammography screening among Canadian women." *Canadian Journal of Public Economics*, 88(5): 346-350.
- Moser, K., J. Patnick, and V. Beral. 2009. "Inequalities in reported use of breast and cervical screening in Great Britain: analysis of cross sectional survey data." *BMJ: British Medical Journal*, 338: b2025.
- Pol, M van der. 2011. "Health, education and time preference." *Health Economics*, 20: 917-929.
- Schneider, S. L. 2008. The application of the ISCED 97 to the UK's educational qualifications. In: Schneider, S. L. (ed.) 2008. The International Standard Classification of Education (ISCED 97). An Evaluation of Content and Criterion Validity for 15 European Countries, pp. 281-300. Mannheim: MZES.
- Stout, N. K. et al. 2006. "Retrospective Cost-effectiveness Analysis of Screening Mammography." *JNCI Journal of the National Cancer Institute*, 98(11): 774-782.
- Train, K. 2009. *Discrete Choice Methods with Simulation*. Cambridge University Press, 2nd edition.

Uhlig, S. C. N. 2008. "The Nature and Causes of Attrition in the British Household Panel Survey." *ISER Working Paper Series*, No. 2008-05.

Warner, J. T. and S. Pleeter. 2001. "The Personal Discount Rate: Evidence from Military Downsizing Programs." *The American Economic Review*, 91(1): 33-53.

	mean	standard deviation	observations
age	56.56	4.28	25,453
married	0.71	0.45	25,453
widow	0.08	0.27	25,453
has children	0.88	0.32	24,584
white	0.98	0.15	22,248
works	0.51	0.50	25,453
secondary education only	0.52	0.50	25,242
higher education	0.08	0.27	25,242
financial difficulties	0.32	0.42	25,402
smoker	0.25	0.43	23,766
good health	0.64	0.48	23,761
chest problems	0.14	0.35	25,438
stomach problems	0.11	0.31	25,438
diabetes	0.04	0.19	25,438
GP visits (categories from 1 to 5)	2.63	1.25	25,396
dental check-up	0.65	0.48	25,426
Wales	0.15	0.35	25,453
Scotland	0.15	0.36	25,453
Northern Ireland	0.11	0.31	25,453

Table 1: Descriptive statistics, pooled sample of women aged 50-64

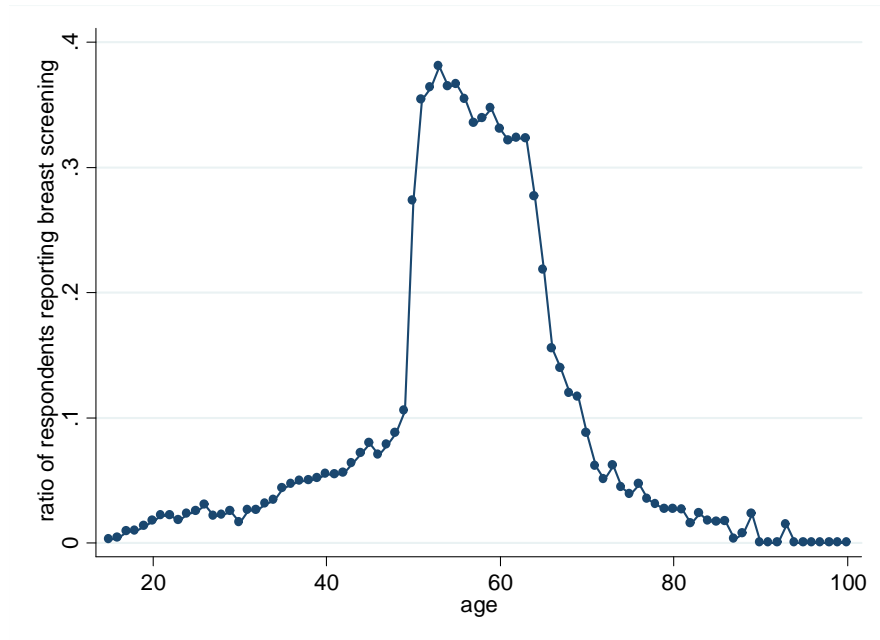


Figure 1: Breast cancer screening attendance by age

	(1)	(2)	(3)
secondary or higher education	0.054*** [4.09]	0.037** [2.47]	0.021 [1.41]
age	0.002* [1.64]	0.002 [1.10]	0.003* [1.86]
work		0.011 [0.74]	0.014 [0.95]
married		0.089*** [5.67]	0.085*** [5.55]
widow		0.059** [2.19]	0.058** [2.20]
has child		0.021 [1.05]	0.018 [0.88]
white		0.066* [1.68]	0.069* [1.77]
financial difficulties		-0.019 [1.48]	-0.018 [1.42]
smoker		-0.067*** [4.34]	-0.051*** [3.42]
chest problems		0.024 [1.28]	0.014 [0.72]
stomach problems		0.007 [0.33]	-0.012 [0.58]
diabetes		0.017 [0.46]	0.011 [0.29]
Wales		-0.025 [1.36]	-0.025 [1.39]
Scotland		-0.054*** [3.19]	-0.050*** [3.03]
Northern Ireland		-0.040 [0.42]	-0.069 [0.70]
good health		0.006 [0.42]	0.043*** [2.99]
GP visits (1-5)			0.036*** [6.42]
dental check-up			0.086*** [6.47]
Constant	0.193*** [2.94]	0.102 [1.13]	-0.117 [1.28]
Observations	9,687	8,004	7,996
R-squared	0.00	0.02	0.03

t statistics in brackets based on cluster standard errors

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2: Reduced form estimation results of attending a due mammography (OLS estimates)

	Coefficients		Average marginal effects	
	1-yr survival	2-yrs survival	1-yr survival	2-yrs survival
screening	0.934** [2.37]	0.524* [1.95]	0.0046*** [2.86]	0.0057** [2.04]
age	-0.106*** [2.88]	-0.099*** [3.24]	-0.0006*** [2.66]	-0.0012*** [3.04]
work	1.057** [2.25]	0.766*** [2.60]	0.0050*** [2.74]	0.0081*** [2.82]
smoker	-0.252 [0.82]	-0.496* [1.78]	-0.0016 [0.79]	-0.0064* [1.63]
good health	0.765* [1.84]	0.577* [1.88]	0.0042** [1.96]	0.0066* [1.92]
GP visits (1-5)	-0.309** [2.21]	-0.305** [2.43]	-0.0019** [2.11]	-0.0037** [2.35]
chest problems	-0.539 [1.64]	-0.623** [2.08]	-0.0036 [1.46]	-0.0086* [1.80]
stomach problems	-0.714** [2.07]	-0.599* [1.92]	-0.0052* [1.69]	-0.0086* [1.63]
diabetes	-0.366 [0.75]	-0.414 [0.84]	-0.0025 [0.65]	-0.0059 [0.72]
constant	11.561*** [5.21]	10.675*** [5.70]		
Observations	7,951	6,897		
Pseudo R ²	0.15	0.13		

* significant at 10%; ** significant at 5%; *** significant at 1%

t statistics in brackets based on cluster standard errors

Table 3: Logit model estimation results of survival

DISUTILITY PARAMETERS ($u_0(.) - u_1(.)$)		
age	-0.005*** [2.97]	-0.004*** [5.88]
secondary or higher education	-0.188*** [2.62]	-0.177*** [2.56]
married	-0.388*** [4.18]	-0.390*** [4.79]
good health	-0.031 [0.35]	-0.037 [0.40]
smoker	0.405*** [3.40]	0.407*** [4.38]
Scotland	0.369*** [3.49]	0.364*** [3.90]
Wales	0.089 [1.07]	
Northern Ireland	-0.039 [0.34]	
Constant	1.258*** [14.35]	1.219*** [12.09]
DISCOUNT FACTOR		
δ	0.691*** [6.66]	
$\delta \cdot$ elementary edu.		0.674*** [6.87]
$\delta \cdot$ secondary or higher edu.		0.758*** [5.17]
* significant at 10%; ** significant at 5%; *** significant at 1%		
t statistics in brackets based on cluster standard errors (corrected for two-step estimation)		

Table 4: Maximum likelihood estimates for the parameters of the disutility of mammography and for the discount factor, based on the model with long time horizon

DISUTILITY PARAMETERS ($u_0(.) - u_1(.)$)		
age	-0.008*** [6.87]	-0.008*** [8.13]
secondary or higher education	-0.183*** [2.85]	-0.179*** [2.71]
married	-0.394*** [3.86]	-0.395*** [6.15]
good health	-0.083 [1.14]	-0.087 [1.47]
smoker	0.353*** [4.90]	0.353*** [4.90]
Scotland	0.230*** [2.75]	0.212*** [3.01]
Wales	0.100 [1.19]	
Northern Ireland	0.164* [1.65]	0.145 [1.29]
Constant	1.456*** [23.61]	1.458*** [17.98]
DISCOUNT FACTOR		
δ	2.014** [2.10]	
$\delta \cdot$ elementary edu.		1.924** [7.96]
$\delta \cdot$ secondary or higher edu.		2.156* [1.89]
* significant at 10%; ** significant at 5%; *** significant at 1%		
t statistics in brackets based on cluster standard errors (corrected for two-step estimation)		

Table 5: Maximum likelihood estimates for the parameters of the disutility of mammography and for the discount factor, based on the model with short time horizon

	Secondary or higher education parameter in the disutility of mammography	Discount factor
(1) GP visits included	-0.175** [2.56]	0.643*** [5.14]
(2) Dental care included	-0.111 [1.15]	0.670*** [4.75]
(3) No exclusion restrictions	-0.192*** [2.61]	0.388 [0.69]
(4) Subjective health excluded	-0.192** [2.47]	0.712*** [7.48]
(5) Repeated and postponed screening	-0.189** [2.15]	0.695*** [3.65]
(6) Time horizon up to age 79-81	-0.188** [2.28]	0.696*** [6.47]
(7) Time horizon up to age 69-71	-0.198** [2.49]	0.850** [1.99]
(8) Estimated survival up to 10 years	-0.184* [1.71]	0.646*** [3.08]
(9) Retirement at age 65	-0.188*** [2.57]	0.682*** [5.71]

* significant at 10%; ** significant at 5%; *** significant at 1%

t statistics in brackets based on cluster standard errors (corrected for two-step estimation)

Table 6: Robustness checks of the maximum likelihood model with long time horizon, selected parameters